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New Opportunities in Computer-Aided Diagnosis: Change Detection and Characterization

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Computer-aided diagnosis (CAD) is an exciting field of investigation that promises to increase the efficiency of radiologists while increasing accuracy. This is of particular interest at a time when the complexity of imaging examinations is rising, the demand for imaging is increasing, and reimbursement is declining.

Traditionally, there have been 2 kinds of CAD: CAD for detection (CADe) and CAD for assigning diagnostic possibilities. We believe that a third member should be added to the CAD family: CAD for change detection and characterization (CAD-CDC). The first 2 types of CAD have been studied for some time, and there is an extensive literature, which we will not review here. Computer-aided diagnosis for CDC is a much younger field that is only beginning to be applied in radiology [1–3].

The basic tenets of CAD-CDC are that using the common or correlated information from 2 time points allows the greater suppression of noise and greater accuracy than is possible when the 2 examinations are measured independently. The second tenet is that it is not necessary to assign specific contours to structures or lesions; only changes in those structures or lesions need be characterized.

When change detection is mentioned, most people unfamiliar with the field think of subtraction. This is a good starting point for discussion. The subtraction of 2 different time points is actually a simple form of change detection, but one that suffers from a high level of noise and low specificity. If more information is available at each time point (eg, magnetic resonance images with multiple contrast properties, computed tomographic attenuation values with different x-ray energies or from different contrast phases), it is possible to suppress noise between 2 time points by using the additional information available from the different image types.

If one can derive information about tissue types, one can also correctly avoid some errors. One example is from brain magnetic resonance imaging, in which white matter with a small amount of edema will signal like gray matter on standard pulse sequences such as T_1-weighted, T_2-weighted, and fluid-attenuated inversion recovery images. However, if on the other time point this tissue was either normal or had enough edema that this mistake would not be made, a change detection algorithm could correctly assign that tissue to white matter with edema rather than gray matter.

One can also suppress noise by requiring consistency within neighborhoods of points: it is unlikely that a single pixel would truly have a change of one type if all its neighbors changed in a different manner. However, if many pixels in a region change in the same direction, this is unlikely to be noise.

The second appeal of CAD-CDC is that precise segmentation is not necessary. The traditional method for measuring the growth of a tumor is to segment the 2 examinations, calculate the volume at each time point, and subtract. This can be a challenge because tumors often have ill-defined boundaries, which will result in uncertainty about the margin. Depending on the algorithm or the human operator, the decision criteria for defining the lesion boundary may be different for each time point, producing apparent change when no real change is present. The poor reproducibility of lesion measurement is well-known and is often in the range of 10%. Computer-assisted methods can reduce this to perhaps 5% for reasonably well-defined lesions.

Change detection does not need to precisely define the boundary, a feat that may not be possible. Radiologists have long used speculated and infiltrative margins as a sign of malignancy, and this lack of a boundary is proven in pathologic studies for many types of tumors. Computer-aided diagnosis for CDC reduces the impact of ill-defined boundaries, because if a boundary is similarly hazy on the 2 examinations, the computer will correctly decide that there is no change. This is a reasonable assumption: whatever effects partial volume artifact has on a given image type should be consistent. Conversely, if a (hazy) boundary shifts, that can accurately be assessed, even if the "true" tumor volume (if such

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a thing exists) is not accurately measured.

The widespread availability of imaging means that an increasing fraction of patients will have prior imaging studies that must be compared. This will continue to increase as imaging is increasingly used for screening purposes. The knowledge present in those examinations can be leveraged with change detection technology.

If the accuracy of the prior examination interpretation can be trusted, a CAD-CDC algorithm could highlight the subset of images in which there is change. Although this is probably not acceptable practice, it could provide "pointers" to locations of change (much like CADe) to minimize the chance that important changes will not be detected. Computer-aided diagnosis for CDC can also help standardize the magnitude of change that is considered significant. It is often difficult to be certain whether minor changes in appearance represent real changes or are related to technical differences in acquisition properties. Computer-aided diagnosis for CDC may be better able to distinguish real changes from artifacts.

It may also be possible to apply change detection technology to examinations for which no priors exist. Image-warping methods could warp an anatomic atlas onto a patient examination. A change detector could then identify regions where the patient examination fails to match accepted profiles for each anatomic region for the examination image types.

Although CAD-CDC represents an important advance in technology, it is critical that the user side not be ignored. As with CADe, the proper presentation of the algorithm results is critical to maximizing the advantage gained. There are 2 important aspects of the image manipulation that make the presentation a bit more complicated than for CADe. First, CAD-CDC typically requires some sort of alignment between old and new studies. That raises the question of whether the nonaligned old study should be displayed for visual comparison, or the aligned. In several studies, radiologists using aligned images are more accurate and more efficient. We also believe that new modes of presenting these aligned images will further increase the benefit.

The second aspect of presentation is that CADe has a single type of output: "a lesion may be present at this location." For CAD-CDC, each location may be unchanged, or changed in any of a number of ways, namely, the permutation of the tissues involved. In the case of cancer, the tissues would be normal, tumor, peritumoral edema, and necrosis at a minimum. Because any of these could progress to any other (except for necrosis turning back to tumor or normal), there are 12 possible transitions. Furthermore, there are degrees of change for each of these 12 transitions (eg, a little edema progressing to a lot of tumor, or mostly tumor going to normal). Representing all this information in a compact form has been a challenge in our testing. In a more recent version, we have reduced the 12 transitions back to 2: good change or bad change. These are represented as red or green overlays on the postcontrast image, with the intensity indicating the magnitude of change. The user may toggle the color overlay on and off to see the underlying image data. Although this presentation mode seems an improvement, the benefit has not yet been documented.

Computer-aided diagnosis for CDC is likely to become a common technology in the next 5 years. It will begin with tools to allow alignment of old and new imaging studies. Tools to subtract these (much like DSA) may then be applied. True CAD-CDC will come shortly after that, as the complexity of data sets demands more than what subtraction can provide.

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